Investigation of genetic operators and priority heuristics for simulation based optimization of Multi-Mode Resource Constrained Multi-Project Scheduling Problems (MMRCMPSP)

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ABSTRACT

Solving NP-hard Problems like Multi-Mode Resource Constrained Multi-Project Scheduling Problems (MMRCMPSP) needs efficient search and optimization strategies. The combination of different approaches such as a meta-heuristic (Genetic Algorithm) for the mode assignment and a Heuristic (Priority Rules) for the job selection allows a 2-step solving-process. In this paper, we present such an approach for solving MMRCMPSP implemented with a simulation-based optimization tool. We investigate the influence of specific parameters of the algorithm to figure out which parameters mostly affect the result of MMRCMPSP.

INTRODUCTION

Organizations deal with different sorts of projects subjected to various variables and constraints. The basic principles in project management are the same but they cannot be applied on every organization due to their divergent production layouts and needs. Richard P. Olsen (1971) defined in his article "Can Project Management Be Defined?" project management as "…the application of a collection of tools and techniques to direct the use of diverse resources towards the accomplishment of a unique, complex, one-time task within time, cost, and quality constraints. Each task requires a particular mix of these tools and techniques structured to fit the task environment and life cycle (from conception to completion) of the task."

Resource constrained scheduling is a class of project management problem concerning limited availability of resources which was initially defined by Conway et al. (1967) and later on was further extended by Brucker et al. (2004). The state-of-the-art extension of taxonomy and division can be found in Zahid et al. (2015).

The current paper deals with the extended version of such constrained scheduling problems by means of creating models which are able to reproduce characteristics of real time production floors. It is known as Multi-Mode Resource Constrained Multi-Project Scheduling Problem (MMRCMPSP).

The two widely known generalizations of modelling multiple modes are (1) an activity with requirement of multiple skills available with various resources (2) change in activity duration time with different quantity of resource. For detailed definitions and variations for MMRCMPSP, we refer to the research provided by Kuster et al. (2007).

In complex industrial environments with a variety of orders and resource limitations, scheduling is an NP-hard problem (Bowman, 1959), even if it is to find a feasible one. This class of problem is characterized as NP hard because of various reasons:

- Integer variables
- Non-convex problems
- Lack of exact solution methodologies

Many scheduling algorithms have been presented in past literature and a few basic techniques can be reviewed in a journal by Kolisch et al. (1995) in which they emphasized the need of computational efficiency for solving large scale problems. With changing customers' requirements and technology, objectives of the companies have been evolved and have multiple dimensions which impose limitations on using traditional search techniques for near optimal results. Solution methodologies for these can be divided into four main types (Brucker, 2004):

Relaxation: The problems are solved by relaxing some parameters.

Approximation: These methods solve the problem close to original one but do not guarantee global optima. These include commonly heuristics methods usually applied on large scale problems.

Expert Systems: These are increasingly gaining popularity for solving NP-hard problems. They usually combine the advantages of enumeration and heuristic methods.

Enumeration: These methods guarantee global optima but are found difficult to apply in case of large variables. Examples include B & B and Dynamic programming.

Apart from these solution methodologies, simulation methods and graphical techniques are also being applied

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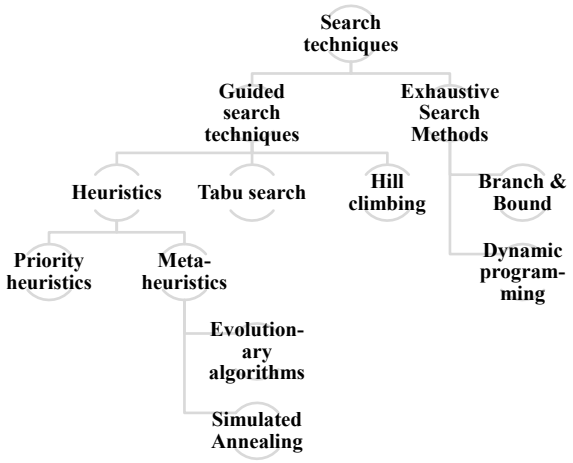
in this area with the main focus of attaining an acceptable optimal schedule in a feasible time for complex production systems. However, studies mostly seem to focus on one expect of the problem, which is either to find better search algorithms for optimized results or on the development of models.
This paper uses MMRCMPSP model where each resource has various skills required to perform tasks. This way of modelling not only enables decision managers to use various options of shifting activities to a different renewable resource available at the time but also narrates the real time production floor in a better way. On the contrary, it also complicates the problem by increasing the decision variables since apart from the decision of allocating start time for the tasks, assignment of particular resource needs to be done as well. In the next section, review of search techniques in this area has been provided before describing the proposed simulation based optimization strategy.

LITERATURE REVIEW

Due to the number of limitations which came across for using exhaustive search (based on searching the complete search space), scientists were prone towards guided search techniques. The figure below (Zahid, T., 2013) depicts the overview of search techniques for optimization which have been explored so far in the manufacturing industry.



Figures 1: Classification of Search techniques

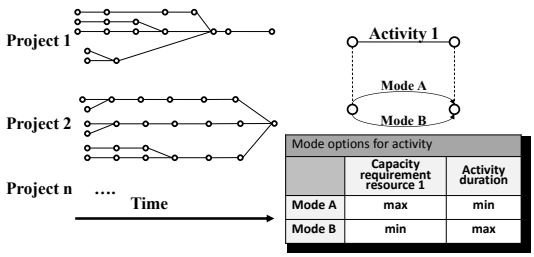
The research area regarding heuristic solution techniques dominates exact approaches in this area. The basic reason is the problem of complexity faced in RCPSP and its variants while solving large scale problems where exact approaches are unable to find solution with accepted computational time.
The most famous commonly used approach in this area is constructive heuristics which uses priority rules with parallel or series schedule generation schemes. Various types of priority rules have been applied and discussed in literature. These most commonly used greedy priority heuristics are used as a decisive tool to allocate limited resources to tasks.
In a similar study on heuristics (Myszkowski et al. 2013) conducted on new data set developed with the help of Volvo-IT department in Wroclaw. They concluded that resource based priority rule perform the worst and slack based measures were simple in calculations and provide better performance results. In another research (Buddhakulsomsiri and Kim 2007) FIFO was concluded as the best in case of maximizing number of finished products while shortest processing times rule (SPT) performed better with the objective of maximum machine utilization. The comparison of famous priority rules can be seen in an article by Iringova et al. (2012). Another comprehensive study in this regard can be seen in the article by Boctor (1993) who studied state of the art priority rules with respect to different manufacturing layouts. In a research conducted by Kühn et al. (2015), sensitivity analysis was performed to measure the impact of priority rules on various factors of a single performance measure.

With the increase of problem scale and need to extend these optimization techniques to real scale problems, numerous meta-heuristics like simulated annealing (SA), ant colony (ACO), genetic algorithms (GA) and particle swarm optimization (PSO) have been explored to speed up the optimization process. GA is most popular in this regard. GA based decomposition was proposed by Vanhoucke et al. 2013. However, this decomposition was used for optimization of schedule. First the whole schedule was created and then a random part of the schedule was selected for optimization and after achieving the target value, was remerged into the complete schedule. Cheng et al. (2012) used a simulation based GA approach for similar problem with the addition of time based resources.
However, GA involves the use of several parameters to search in the solution space with a random distribution such as selection pressure, crossover and mutation rate. In the light of state-of-the-art research, this investigation focuses on the question “How do the GA parameters effect the search direction in correspondence with various priority heuristics?” Among several heuristics, best considered in past researches have been chosen and investigated in combination with GA. As in a conducted study on MMRCMPSP (Kuster, 2007), it was concluded that GA techniques mostly seem to show higher rate of improvements in the first simulation runs which is why good initial solutions are of significant improvement for solution quality. Thus, the present research proposes to investigate priority heuristics and GA in concurrent. In the next section, model and design of experiments would be described in detail for the readers.

MODEL AND PLATFORM

Model
The case study is based on a complex assembly line for the production of printing machines and therefore, attributable to the mechanical and plant engineering and is implemented through a case study. The production system involves different orders considered as separate

projects with individual due dates (Multi-Project-Problem). Every product is an independent project which includes specific product, resource and process information. The individual network of each project is presented as an activity-on-arc network. An activity requires specific qualification/skills for execution, fulfilled by various resources (Modi-Problem). This information is summarized as options in a qualification table (Fig. 2) based on the work of Carl and Angelidis (2015). Following paragraph describes the constraints and variables which were modelled according to the above described production plant requirements.

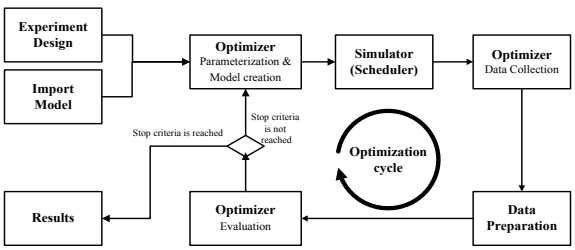


Figures 2: Multi-Mode- and Multi-Project-Problem

Three types of staff resources are considered in this model based on a case study (e.g. electrician, logistic) and each renewable resource is defined via a set of skills/qualifications. In total there are 9 internal workers (assumption: available 24 hours) in addition to the possibility of one subcontracted worker for each resource with increased cost. Equipment (Crane in this case) is also added with possibility of renting another one at an additional cost. The considered scenario includes 10 sales orders with a total of 13 products. The time horizon for production plan is 20 days. Each product has an own due date and cost rate for delay and earliness. The total activities are 2700 which can be performed with a maximum of two modes. There is a range of 126-276 activities to produce for a single product where the activity duration varies between 11 and 400 minutes.

Platform

Simulation based optimization is widely used to get fast optimized solutions in large search spaces such as for the above described problem class. A platform which implements this theory was developed by Angelidis et al. (2013) and is called SBOP (simulation based optimization platform). The optimization cycle is shown in figure 3.



Figures 3: Scheduling with simulation based optimization (Based on Angelidis et al. 2013)

The first step is the transformation of the real system to the manufacturing model. The models describe all necessary production information as previously described in the model part. The optimizer has 3 functions: (1) parameter setting for creation of various simulation models (2) data collection (3) evaluation by calculating the interested key performance indicators. If the stopping criteria are not met, the optimization process continues.

In the later section, optimization objectives and optimizer used for the current simulation would be explained.

Optimizer

In a manufacturing environment, various conflicting objectives are desired for example production cost and production time. For this, production managers need to find the compromise between these conflicting objectives for optimal results. To simultaneously optimize the multi-objective problem, we developed a multi-objective genetic algorithm which (1) utilizes classical Pareto ranking approach to determine the non-dominated solutions (2) introduces methods for diverse population. We will briefly describe the features of this algorithm as follows.

(1) Pareto ranking approach:

It utilizes the Pareto dominance concept (Alvarez-Benitez et al. 2015) to compare the solutions in order to determine the non-dominated solutions in the solution space. In this algorithm we use the Fast Non-dominated Sorting Genetic Algorithm approach referred to Deb et al. 2002.

(2) Customized genetic algorithm to produce diverse population:

(2.1) Chromosome representation (figures 4)

In this study, to represent a simulation model MMRCMPSP, we have used the encoding where each chromosome is made of n genes, where n is the number of the activities.

$$\text{Chromosome} = \underbrace{(\text{gene}_1, \ldots, \text{gene}_n)}_{\text{Mode of activity}}$$

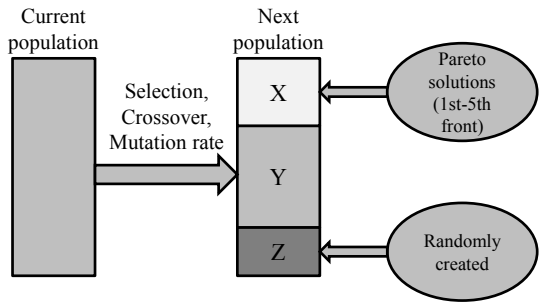
Figures 4: Chromosome representation

(2.2) Population formation (figures 5)

To make a trade-off between convergence speed and diverse population, we have applied a special strategy.

A population consists of three parts. The individuals of the first part are obtained from the non-dominated solutions (from the first front to the fifth front solution) discovered by the GA which is considered as an elitist method (X). We use a parameter 'copy rate from pareto' to represent percentage of population copied from non-dominated solutions. The individuals from the second part are created randomly. It is described by another parameter 'rate of random selection' (Z). The

individuals of the third part come from the previous population via selection, crossover and mutation (Y). The following is an example to demonstrate how to form a population. Supposed the population size is 100, the 'copy rate from pareto' is 0.2 and the 'random created rate' is 0.1, which means 20 (100*0.2) individuals are copied from the non-dominated solutions, 10 (100*0.1) individuals are created randomly, and the rest 70 (100-20-10) individuals are created from the previous population.



Figures 5: Formation of population

(2.3) Selection method

We use rank-based roulette wheel selection (Kumar and Jyotishree, 2012) to select individuals as parents to create off springs. The mapping function *g(pos)* of the ranks of individuals for determining their selection probability is as follows:

$$g(pos) = 2 - 2 * (SP - 1) * \frac{pos-1}{n-1} \quad (1)$$

Where *SP* is the selective pressure that is considered as one parameter of the GA ($1 < SP \leq 2$), pos is the position of the sorted individual in the population P, *n* is the number of the individuals in the population. This means the higher the position of an activity, the higher rank the activity has.

(2.4) Crossover method

In this algorithm we employ parameterized uniform crossover (Jaddan et al., 2015) to create offspring. After two individuals are selected as parents, at each gene a biased coin is tossed to determine which parent will transmit the gene to the offspring. It assumes that a toss of head will choose the gene from the first parent, and a toss of tail will select the gene from the second parent. The following table shows the mode selection for a tail rate of 0.3. It means that the probability to toss a tail is 0.1-0.3 while the probability to toss a head is 0.4-1.0.

Table 1: Crossover method

Coin toss	Head (0,5)	Tail (0,1)
Parent A	Mode 1	Mode 3
Parent B	Mode 2	Mode 4
Child	Mode 1	Mode 4

(2.5) Solving genetic drift problem

Due to multi-dimensional search space, multi-objective genetic algorithm has an inherent characteristic called genetic drift. The population tends to form relatively few clusters that prevent diverse population. In order to increase diversification, we have utilized the concept of density estimation by means of calculating the total Euclidean distance (figures 6) of a solution to other solutions in the same Pareto front.

The first step is to calculate the Euclidean distance for every solution pair *x* and *y*.

$$z(x,y) = \sqrt{\sum_{k=1}^{k}\left(\frac{Z_k(x)-Z_k(y)}{z_k^{max}-z_k^{min}}\right)^2} \quad (2)$$

with

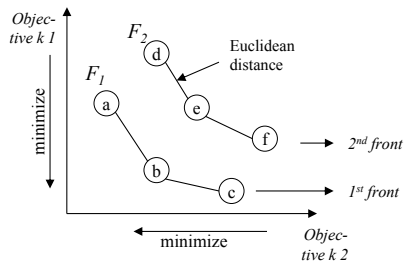
k : amount of objectives

z_k^{min}, z_k^{max} : Maximum and Minimum value of objective function z_k observed so far.

The second step is to calculate the total distance *TD* of solution *x* to other solutions *t* of population *P* (eq. 3) while the third step is to adjust fitness of solution *x* (eq. 4):

$$TD(x,t) = \sum_{t \in P} z(x,t) \quad (3)$$

$$f'(x) = \frac{pos}{TD(x,t)} \quad (4)$$



Figures 6: Euclidean distance in Pareto fronts

In this study, the considered optimization objectives are minimizing (1) total cycle time C (sum of cycle time C_j of each product *j*), (2) total tardiness T (sum of tardiness T_j of each product *j* referred to the due date d_j), and (3) total costs M (activity-based costing, Cost M_j for manufacturing a product *j*).

$$C = min \sum_{j=1}^{J} C_j \quad (1)$$

$$T = max \sum_{j=1}^{J} (C_j - d_j, 0) \quad (2)$$

$$M = min \sum_{j=1}^{J} M_j \quad (3)$$

where;

j Product (j=1…J)

The unit of tardiness and cycle time is time unit (TU), the unit of costs cost unit (CU).
The applied cost function is a result of the research project of Carl and Angelidis (2015).

COMPUTATIONAL EXPERIMENTS

For answering the research question we conduct computational experiments. The investigated input parameters of the optimizer and the associated DOE is shown in the following table:

Table 2: Full 3-level factorial plan

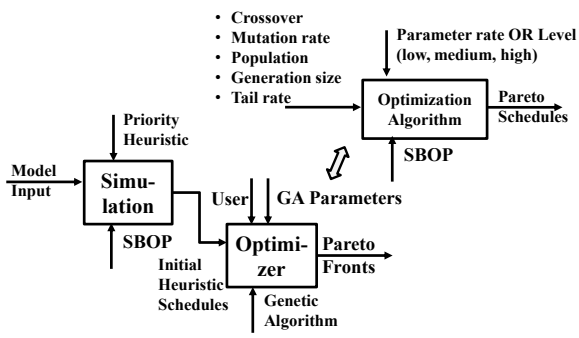
	Low	Medium	High
GS	10	30	50
PS	10	30	50
CR	0.1	0.5	0.9
MR	0.1	0.5	0.9
TR	0.1	0.5	0.9

GS=Generation size, PS=Population Size,
CR=Crossover, MR=Mutation rate, TR=Tail rate

Each parameter of the optimizer is investigated with 4 different priority rules, which are:

- First in First out (FIFO)
- Earliest operation Due Date (ODD)
- Minimum Slack (MSLK)
- Shortest processing time (SPT)

So we apply a 3-level plan for the 4 different priority rules which becomes a total of 972 design experiments described by an IDEF diagram in figure 7.



Figures 7: Experiment design

The amount of simulation runs for each experiment depends on the parameters generation size and population size. So one experiment can have in our example up to 2500 simulation models (GS=50, PS=50). So all in all the experiments took 12 days on an 2,49 GHz Intel® Xeon processor with 24 GB RAM.
For each experiment, the best schedule according to the fitness-value f´(x) is selected for the investigation.
The following table shows an overview for the results of the best schedules from each experiment:

Table 3: Results of Experiment Runs

	Tardiness (TU)	Cycle Time (TU)	Costs (CU)
Average	2693.37	5456.11	332503.3
Standard deviation	20.34	47.7	818.35
Minimum	2607	5305	322663.9
Maximum	2751	5569	334862.8

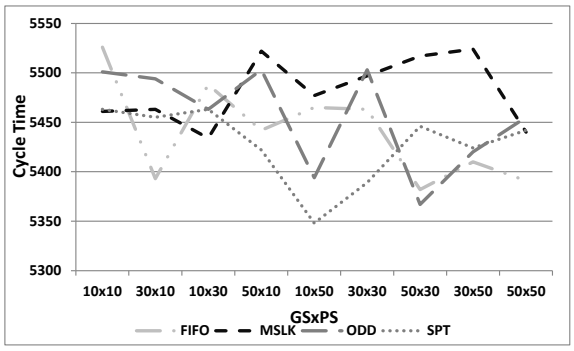
If we have a look on the results, there are significant differences between the minimum and the maximum values for the objectives. To find out which parameter has the strongest influence on the objectives, we have performed a sensitivity analysis.

The following table shows the main effects of the parameters on the single objectives (uncoded parameters). The main effect of a factor is defined as the average change in the output, which is generated by conversion of this factor from a level to the next higher level (for priority rules from random rule to specified rule).

Table 4: Results of Experiment Runs

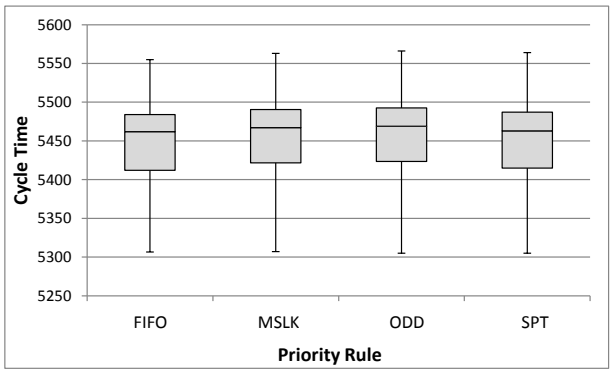
	Tardiness (TU)	Cycle Time (TU)	Costs (CU)
GS	-3.356	-22	-912.8
PS	-15.6	-32.2	-995.98
CR	1.17	17.30	311.26
MR	11.08	4.33	382.92
TR	2.43	6.29	119.28
PR FIFO	-1.1764	-24.18	-65.22
PR MSLK	7.0108	22.5	240.87
PR ODD	1.1842	13.41	142.46
PR SPT	-7.0185	-11.74	-318.12

Table 4 shows that GS and PS are minimizing the objective functions when they are increased while CR, MR, TR are maximizing the objective functions when they are increased. For the usage of the priority rules, the impact on the objective function is different and not so significant. On ranking the impact we observed that in general, GS and PS have maximum influence on objectives although, detail analysis shows that it is not necessary to have continuous improvement by increasing GS and PS. It can be observed in the figure below that with increased GS and PS levels, cycle time does not shows continuous improvement (CR=0,1, MR=0,1 and TR=0,1):



Figures 8: Cycle time to priority rules and GSxPS

The figure shows that it´s possible to get with any priority rule good results, but not according to a specific parameter combination. The only exception is MSLK, where results are generally poor. With more simulation runs it tends to better results. So the question is how to get with a high probability good results when choosing a priority rule. For this investigation, we must have a look at the distribution of results, shown in the following figure for cycle time as a box-plot whisker diagram.



Figures 9: Cycle time to priority rules

The median of FIFO and SPT is lower than for MSLK and ODD. For FIFO and SPT, the lower quartile has a wider range than for MSLK and ODD, what means that the possibility to get better results is higher when using FIFO and SPT. Another presumption is, that for this priority rules the impact of the other parameters is much lower. So that means, when we are using SPT or FIFO, it is more likely to get high-quality results with fewer simulation runs. This presumption is part of our further research.

CONCLUSIONS

In this paper, we have investigated various parameters for solving and optimizing the MMRCMPSP, especially the problem domain of complex assembly lines. For solving and optimizing, we used a platform based on the theory of simulation based optimization. GA was used for optimization purposes with initial population generated from priority heuristic scheduling. These two strategies are part of the developed and presented optimizer. The investigation is based on a case study. We tried to find out, which genetic operators have the strongest influence on the search direction of the genetic algorithm regarding the objectives tardiness, cycle time and costs. So we used a 3 level plan for the GA-parameters which were observed in combination with the priority rules. It was observed that GS and PS have the biggest influence on the objective function. Priority rules have different impacts. The probability to get the best result is most likely, when PS and GS are maximal and CR, MR and TR is minimal. For this model, we get the more high quality results from FIFO and SPT without considering the parameters of GA. Hence, conclusion that can be drawn is that in case, priority heuristics provide poor initial population, higher optimization runs have to be performed for the same results obtained from better initial solutions via better priority rules. Our further investigation will concentrate on methods to find the optimal parameter setting, to get a good trade-off between run time and results. We will also investigate the performance of priority rules in case of different production layouts.

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